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THESIS

ANALYSIS OF THE RELATIONSHIP BETWEEN DEMAND
AND CARCASS RETURNS AT THE NAVY SHIPS' PARTS
CONTROL CENTER

by

Robert Bruce Vassian

September 1991

Thesis Co-Advisor:

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David B. Wadsworth

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An Analysis of the Relationship between Demand and Carcass returns at
the Navy Ships' Parts control Center

by

Robert Bruce Vassian
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Submitted in partial fulfillment of the requirements for
the degree of

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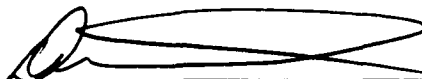
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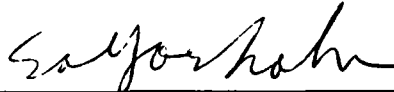

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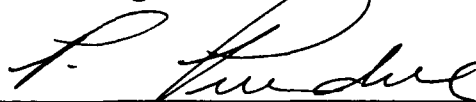

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ABSTRACT

This thesis examines the nature of the repairable part demand-carcass return relationship at the Navy Ships' Parts Control Center and proposes an alternate forecasting method for predicting the number of carcasses arriving at the Depot Overhaul Points in the coming quarter. The analysis begins with graphical and correlation review of the variables and then uses regression, and exponential smoothing to model carcass returns. These methods are compared to the model currently in use by an analysis of the forecasts errors. The comparison suggests that the exponential smoothing model results in the most accurate forecasts. The thesis concludes with some recommendations for model implementation.



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I. INTRODUCTION

A. BACKGROUND

The Navy Ships' Parts Control Center (SPCC) is the cognizant Inventory Control Point (ICP) for all non-aviation consumable and repairable spare parts. Given the number of applications in the fleet, the demand history, and any known technical information/problems associated with a particular part, the Inventory Manager (IM) can reasonably predict the number of parts required for the short run future, over the next four quarters. This forecast requires the IM to specify the manner in which a part will become available to fleet units when requested: 1) stock on hand, 2) new procurement contracts, or 3) a repaired unit from Navy organic or commercial Depot Overhaul Points (DOPs). Efficient management of repairables requires SPCC to forecast repair quantities at the DOPs. The limiting factor for the number of repairs, is generally the quantity of carcass returns to the depot(s). Once a repairable item is determined to be faulty, it is pulled out of the mechanical/electrical system and the ship or station requisitions a Ready for Issue (RFI) replacement. When the requisition is forwarded into the supply system, a demand is registered at SPCC. Although the unusable component is supposed to be shipped off-station at the time of requisitioning, the carcass can take two to three quarters to arrive at the DOP. This uncertainty in carcass return quantities makes it difficult for SPCC to budget for repairs.

Currently, SPCC uses the *naive method* (demand from the previous quarter factored by repair survival rate and wearout rate) to determine the

quantity of a particular repairable to use in repair budget calculations and inventory level determination [Ref. 1:p. 3-A-31]. Unfortunately, this estimate is a gross simplification of the carcass return process, widely variable, and leads to inaccurate budget estimates. Although funds can be reallocated during the course of a fiscal year, a good estimate of the number of carcass returns would assist planning in both the budget and inventory arenas [Ref. 2].

SPCC recognizes that carcass returns are a function of more than just the previous demand observation, but has not investigated the relationship. Intuitively, the quantities of demands and carcass returns from several previous quarters directly influence the number of carcass returns which can be expected at the DOP in the coming quarter. The ICP weapon system file holds the past eight quarterly observations for these variables, and is easily accessible to an IM or budgeteer for purposes of forecasting the quantities of carcass returns for particular stock numbered part.

B. OBJECTIVES

There are two objectives of this thesis. The first is to explore and delineate relationships between selected data elements contained in the SPCC repairable data file. For purposes of analysis, a snapshot of this file was taken of approximately 80,000 repairable items and contained the following data fields:

Demand - eight past quarters.

Carcass returns- eight past quarters.

Net Price - price to customer with a returned carcass.

Standard Price - price to customer without a returned carcass.

Repair Price - contractual cost of repair.

Wearout Rate - (or 1 - survival rate) from repair process.

Mark Code - classification by quarterly demand and cost.

The second purpose is to compare different forecasting methods to predict carcass returns at the DOP. The naive method will be used as a basis for comparison of the effectiveness of the forecasting techniques.

C. PREVIEW

Chapter II will describe the repairable carcass return process and, Chapter III will briefly examine the general layout of the data file and establish the relationships upon which this thesis is based. Chapter IV will detail different forecasting methods, discuss, and compare their results. Chapter V will summarize the previous chapters, present conclusions and make recommendations regarding further research.

II. SYSTEM DESCRIPTION

When a new combat system is introduced into the Navy, the method of support must be clearly defined. Secondary items generally fall into two categories: a) repairables - items which can be reworked or overhauled and put back into service, and b) consumables - items which are discarded upon failure. Initial expense and ease of procurement/production are concerns that the system command ponders when the weapon/combat system maintenance plan is being developed [Ref. 1:pp. 3-58-59]. The maintenance plan not only declares that an assembly/ part is repairable, but also specifies the location where the repair is to be accomplished. The Weapon System Planning Document (WSPD) declares the number and location of all current and future systems in fleet use, and projects the funded annual employment of an average system.

A. ICP PERSPECTIVE

It is important for both the IM and the SPCC budgeting sections to be able to estimate the number of Not Ready For Issue (NRFI) carcasses that will be repaired in the coming quarter. Inadequate amounts of funds allocated for the repair of a part/system can cause delays in the initiation of repair and fulfillment of customer requirements. Additionally, the ICP must reallocate funds from other areas. If too much money is slotted for the repair of repairables, other ICP functional areas suffer.

In addition to the system maintenance plan and WSPD, the IM uses technical data about system/component failure rates, production and

procurement leadtimes, available (RFI and NRFI) assets, historic demand and carcass return data to take action to fill customer requisitions. Figure 1 illustrates the dynamics of the repairable material flow process. The IM must satisfy all: a) recurring demand (customer demands generated by in use failures and stock replenishment; b) initial outfittings and allowance changes; and c) parts needed in the repair of a higher level assembly. Possible sources of supply to fill requisitions for repairables are: a) procurement contracts, b) supply system stock on-hand, and c) items being repaired at the DOP. Efficient management of the repair process is essential to the item manager since, in

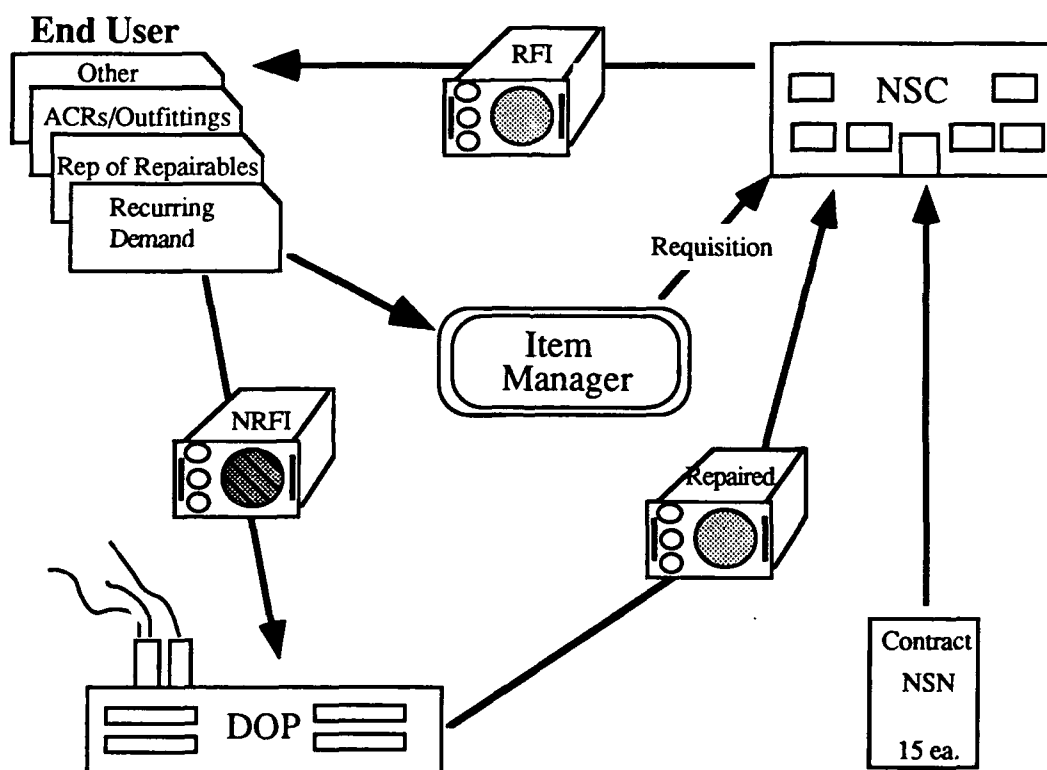


Figure 1 - Requirements and Sources of Supplies

many cases, he/she will only be able to maintain adequate system stock of a particular part by receiving repaired items from the DOP.

When the IM reviews the requirements needed in the near future, a critical piece of information is the number of NRFI carcasses which will arrive at, and be repaired by the DOP. In the long run, this number is simply the quantity of demand, less items which are lost or damaged beyond repair. In the short run, however, carcasses arrive at the DOPs in a less deterministic pattern. Currently, SPCC uses the demand quantity for the previous quarter for an estimate of the number of carcasses expected to arrive at the DOP. In reality, the NRFI part may take several quarters to arrive at the repair location. This time lag is possibly created by remote locations of end users unexpedited shipments/transshipment, etc. Once an item arrives at and is registered on the records of the DOP, the repair process can be managed and, if necessary, expedited. The one missing piece of information from the IM's perspective (other than a deterministic demand figure) is the number of NRFI carcasses that will be available for repair in a given quarter.

B. MATERIAL FLOW

A review of the requisition-material flow process can highlight some of the reasons for the randomness of the carcass returns to the DOP. The process starts with a demand for a part by the end user. The end-user's requirement is satisfied by RFI assets on hand at the time of the requirement, or by new/repaired material received into the supply system after the requisition has been backordered. Replenishment of stock levels primarily comes from the repair of repairable items at the DOPs.

The IM has facts or good estimates concerning the demand-carcass return process. For example the IM knows historical demand patterns, repair turn-around time (RTAT), program requirements, and inventory levels. He does not

know, however, the number of carcasses he can expect to show up at the DOP for repair. The lack of this information affects the size of the new procurement contract since additional safety stock must be ordered to cover the uncertainty of the carcass returns and subsequent repairs..

The NRFI carcass should be shipped back to the DOP at the time the requisition is submitted into the supply system. There are numerous reasons for possible delays. For example:

- a) The ship may be out to sea and cannot return the carcass until it arrives in port.
- b) The carcass is left in a system, to allow the system to operate in a partial capability mode, and will be turned in upon receipt of an RFI asset.
- c) The carcass is turned over to a tanker during refueling in the Indian Ocean. The tanker will turn in the carcass upon return to overseas port.

The item manager can review lists of every outstanding requisition, wholesale system RFI assets available for issue, and wholesale system NRFI assets in or available for induction into the repair process. Parts held onboard a ship, or in the transportation pipeline are "invisible" (not on the SPCC's files) and difficult to track. The best that an IM can do, is to make an intuitive guess as to the number of NRFI carcasses that will arrive at the DOP in a given time period.

As a preliminary step to modelling carcass returns, the next chapter discusses the structure of the raw data used for this thesis, establishes the data fields and variables, and examines some of the basic relationships between the variables.

III. DATA OVERVIEW

This chapter begins with a description of the SPCC repairable item data tape, and examines some of the relationships between data elements/ variables. Data highlights from the preliminary review and grooming of the data set will be discussed. The third section covers the initial examination of the correlation between the variables in the data set.

A. DATA FILE DESCRIPTION

The file used for purposes of this thesis was extracted during March 1991 by the Fleet Material Support Office, Mechanicsburg, PA, and contained eight past quarter data for all 7G, and 7H cog items. The data elements contained on the tape were (listed with data element number (DEN), the number SPCC uses to standardize reference to the data fields in its major files):

Field Name	Card Column	DEN	Type
NIIN	1-9	D046	Character
4 Digit COG	10-13		Character
Mark	14		Integer
FGC	15-18	C001A	Character
SMIC	19-20		Character
LRC	21-23	B002	Character
Past Quarter	24		Integer
Procurement Leadtime	25-28	B011G	Real
Production Leadtime	29-32	B010G	Real
Demand	33-41	A005	Integer

Carcass Returns	42-50	A005B	Integer
Comm Repair Qty	51-54	B012L	Integer
Comm Rep Days	55-58	B012K	Integer
Navy Repair Qty	59-62	B012G	Integer
Navy Repair Days	63-66	B012H	Integer
Rep TAT	67-71	B012E	Real
Unit Price	72-81	B053	Real
Replacement Price	82-91	B055	Real
Repair Price	92-101	B055A	Real
Net Price	102-111	B059	Real
Blank	112-115		
MCC	116	C003A	Character
FSC	117-120	C042	Character
Wearout Rate	121-124	F007	Real
Rep Survival Rate	125-128	F009	Real

This datafile contained 79,384 usable NIINs, with up to 8 past quarter observations per record. The zero demand items (no demand in the past two years) were discarded and considered of no concern since the vast majority of these items also had zero carcass returns over the same period. There are 27,731 items that experienced at least one demand over the two year period. This data set will hereafter be referred to as DEMAND. The past quarter demand and carcass return observations for a given NIIN will be labelled DM1 through DM8 and CR1 through CR8 respectively. In this case the higher the number assigned, the older the variable. For example DM8 is the variable

containing demand information from the eighth past quarter, while CR2 contains carcass return data from the second past quarter.

The demand and carcass return processes for the majority of the NIINs on file are in a relatively steady state. This means that a snapshot of the observations can be expected to reveal that the two year sum of carcass returns is approximately equal to the sum of the demands. This is generally the case, however, 980 items (of the DEMAND file) met the condition that carcass returns minus demands was greater than or equal to twenty-five and were removed. This possibly indicates that the item is being phased out, or there is a modification program in effect for upgrade of the component. In the creation of the DEMAND file a few data errors and unreasonable demand or carcass return observations were noted. Specifically, items with non-numeric, or extraordinarily high numeric (ie; 999999999) demand and/or carcass return observations, were extracted and not used in any of the analysis. Twenty two of these items were removed leaving the DEMAND file with 26,729 items.

For the remainder of this thesis the following conventions will be followed:

- 1) Each model will attempt to forecast CR1, and the forecasted value will be denoted by $\widehat{CR1}$. DM1 and CR1 cannot be used for prediction purposes since CR1 must be reserved for the evaluation of the effectiveness of the forecasts. In actual practice, however, both variables could be used leading to increased accuracy of the models.
- 2) DM2 - DM8, and CR2 - CR8 will be considered independent variables, although it will be necessary to forecast CR2 and use the model parameters to obtain an estimate for CR1.

B. DATA HIGHLIGHTS

Some preliminary graphical data analysis on a sample of 323 items indicated that all of the count variables, DMi and CRi , have similarly shaped

histograms. Figure 2 shows two representative examples, constructed from the items contained in the DEMAND file.

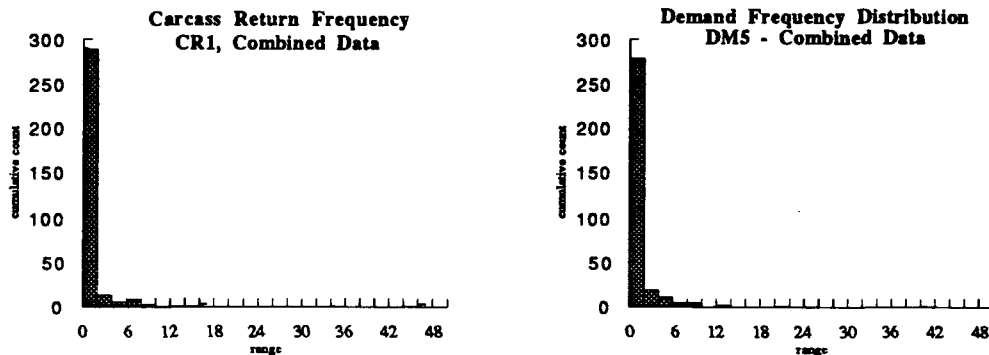


Figure 2 - Representative Variable Histograms

The spike on the left side of each graph is due to the large number of zero observations for CR1 and DM5. This is representative of all of the past quarter DMi and CRi variables. As a starting point to investigate the differences in the types of items included in the file, items were categorized by the quantity of demand observed. This categorization was made to investigate characteristics of items with different demand patterns. Although the MARK Code could be used to segregate demand categories it also incorporates the extended money value for quarterly demand and thus, would not be appropriate to use for this analysis. The categories defined for the remainder of this thesis are:

Combined - All items included in the categories below.

High - Demand ≥ 10 for the two year period.

Med - $4 < \text{Demand} < 10$ for the two year period.

Low - Demand ≤ 4 for the two year period.

The new data sets contained 5784 high (21.6%), 4770 medium (17.8%), and 16175 (60.6%) low demand items. A random sample of 323 items was

drawn and will be used for analysis. The sample's characteristics are shown in Table 1 below.

TABLE 1 - RANDOM SAMPLE CHARACTERISTICS

Category	Number	Percent of Total
High	77	23.84
Medium	57	17.64
Low	189	58.53
Total	323	100.00

Except for the range and dispersion of the variables, the general nature of the histograms did not change using the segregated data sets. Representative graphs are shown in Appendix A, Figures A1 -A3.

All of the demand and carcass return variables, regardless of the demand category, contain a significant number of zeros. This complicates portions of the analysis and will be discussed later.

C. CORRELATION

A preliminary estimate of the correlation between the variables was taken using Pearson product moment correlation. The correlation matrix is presented in Table - 2 and can be seen on the next page, where each entry is the Pearson correlation between the row and column variable for that entry.

No significant patterns can be seen between carcass return variables with a one period lag, demand variables with a one period lag and carcass return-demand variables with a one period lag. All of the correlation figures are relatively high and do not really clarify the relationship between CR1 and the other variables. From Table 2, earlier observations such as DM8 and CR8 could as easily be related to CR1 as DM2 and CR2. This does not intuitively

make sense, since the later carcass returns and demand observations should should exert greater influence on the dependent variable CR1.

**TABLE 2 - PEARSON PRODUCT-MOMENT CORRELATION,
COMBINED DATA**

	DM1	DM2	DM3	DM4	DM5	DM6	DM7	DM8	CR1	CR2	CR3	CR4	CR5	CR6	CR7
DM1	1.000														
DM2	0.825	1.000													
DM3	0.684	0.797	1.000												
DM4	0.555	0.661	0.753	1.000											
DM5	0.687	0.796	0.879	0.714	1.000										
DM6	0.675	0.797	0.864	0.748	0.854	1.000									
DM7	0.716	0.801	0.814	0.673	0.796	0.831	1.000								
DM8	0.581	0.640	0.721	0.598	0.722	0.752	0.661	1.000							
CR1	0.849	0.809	0.617	0.526	0.580	0.617	0.683	0.629	1.000						
CR2	0.661	0.637	0.688	0.556	0.576	0.630	0.654	0.537	0.654	1.000					
CR3	0.299	0.338	0.383	0.347	0.357	0.351	0.322	0.324	0.312	0.367	1.000				
CR4	0.670	0.712	0.801	0.740	0.758	0.800	0.712	0.654	0.604	0.692	0.434	1.000			
CR5	0.773	0.785	0.817	0.685	0.804	0.835	0.759	0.737	0.717	0.711	0.408	0.864	1.000		
CR6	0.660	0.738	0.751	0.633	0.705	0.850	0.809	0.739	0.674	0.641	0.344	0.730	0.791	1.000	
CR7	0.622	0.684	0.712	0.655	0.675	0.743	0.715	0.763	0.690	0.617	0.404	0.711	0.750	0.754	1.000
CR8	0.654	0.739	0.775	0.613	0.780	0.808	0.759	0.638	0.523	0.508	0.273	0.682	0.661	0.678	0.570

For a given NIIN and time, the demand-carcass return process has a finite number of RFI and NRFI carcasses in the supply system. Since this is a closed-loop demand-carcass return process, a high degree of correlation and collinearity exists between the most of variables. The correlation matrix illustrates this point, but is only an indication of pairwise correlation [Ref 3:pp 328-9]. Although it is logical to assume that the first past quarter demand and carcass returns have more importance than the earlier observations, the correlation matrix indicates that there is a high correlation between the CR1, CR2 and the earlier quarters. This is due to the nature of the data, and can be misleading. It seems logical, however, that there would be a one to two quarter lag between demand and carcass return observations. This will be further examined in the next chapter.

D. MODEL COMPARISON

This thesis requires a yardstick of performance of future forecasts. For estimating the relative effectiveness of these forecasts, mean absolute deviation (MAD) and Bias will be used. These measures are commonly used to evaluate forecast models and, if necessary, adjust the model parameters. MAD is an attractive indicator because SPCC currently uses MAD when forecasting demand, which ultimately impacts the calculation of safety stock. Bias will not be used to select the best model, but rather to evaluate model tendencies. The formulas in terms of this problem are:

$$\text{MAD} = \frac{\sum_{i=1}^n |CR1_i - \widehat{CR1}_i|}{n}, \text{ and Bias} = \frac{\sum_{i=1}^n (CR1_i - \widehat{CR1}_i)}{n}$$

where n is the number of items in the sample, $CR1_i$ and $\widehat{CR1}_i$ are the actual observation of carcass returns for $NIIN_i$ and the forecast value of carcass returns for $NIIN_i$ respectively, for the first past quarter.

The MAD will illustrate the size of the forecast error and the Bias will indicate its direction. The MAD, as defined above, is the average error of the individual forecasts of the model. [Ref. 4:p. 45]

IV. FORECASTING TECHNIQUES

This chapter attempts to use regression analysis and exponential smoothing to model the carcass return process. A discussion of pros and cons of each method are discussed.

A. REGRESSION

The first attempt to model the carcass return process was done using the four sample files described in Chapter III. Regression was an attractive method because it could take into account all of the past demand and carcass return observations, while minimizing the squared error term. Another advantage is that regression is efficient and requires few computer resources. Initial regression attempts used all demand and carcass return variables other than the first past quarter to predict CR1. Obviously, DM1 could not be used for prediction purposes, since DM1 and CR1 were observed simultaneously. The intent was to use all of the information available to be able to forecast CR1 with the least amount of error.

It became clear that in order to evaluate the forecasts, the model would have to be fit with the second past quarter as the dependant variable, and then use the regression coefficients obtained to predict the first past quarter. This approach restricts the number of variables available for parameter selection to CR3 - CR8 and DM2 -DM8. In actual practice CR1 would be the dependant variable and all other variables would be used to pick the regression coefficients. Thus the demand and carcass return data from the third to eighth

past quarters were used to obtain coefficients to predict $\widehat{CR2}_i$, as shown in the following equation:

$$\widehat{CR2}_i = \widehat{\beta}_0 + \widehat{\beta}_1 CR3_i + \widehat{\beta}_2 DM3_i + \dots \\ + \widehat{\beta}_{11} CR8_i + \widehat{\beta}_{12} DM8_i$$

where $\widehat{\beta}_0, \widehat{\beta}_1, \dots, \widehat{\beta}_{12}$ are the regression coefficients.

Using the coefficients from the regression, $CR2_i$ becomes:

$$\widehat{CR1}_i = \widehat{\beta}_0 + \widehat{\beta}_1 CR2_i + \widehat{\beta}_2 DM2_i + \dots \\ + \widehat{\beta}_{11} CR7_i + \widehat{\beta}_{12} DM7_i.$$

This forecast simply moves the regression coefficients one period forward and uses $CR2_i$ instead of $\widehat{CR2}_i$, since $CR2_i$ would be have been observed and available for the prediction of $\widehat{CR1}_i$. In actual practice it would not be necessary to do this since $CR1$ would be known, and could be used in place of $CR2$, to predict $CR0$. This should increase the model's predictive capability.

As a preliminary step to the regression of the combined and individual demand category samples, a regression was run using SAS on all 26,729 items in the DEMAND file. Table 3 is the result of this regression and indicates that 33.46% of the total amount of variation was explained by the independent variables. Checking the residuals, with the Kolmogorov D statistic provided in SAS Procedure UNIVARIATE, yielded a p-value ($H_0: \epsilon_i \sim NID(0, \sigma^2)$) < .01 [Ref. 5:p. 1187], which means that the normality assumption concerning the residuals does not hold and that regression may not be appropriate. Examination of the

residuals for the 26,729 stock numbers in the DEMAND file is impractical, but can easily be accomplished for the smaller samples.

TABLE 3 - DEMAND FILE REGRESSION RESULTS

Dependent variable is: CR2				
$R^2 = 33.46\%$ R^2 (adjusted) = 33.43%				
s = 2.37 with 26729-13= 26716 degrees of freedom				
Source	Sum of Square	df	Mean Square	F-ratio
Regression	76619.43	12	6384.95	1136.7
Residual	152378.36	26716	5.62	

The next step was to regress the combined and individual category samples and examine the output. Table 4 shows that more of the variation found in the combined sample can be explained by the regression equation. The regression

TABLE 4 - COMBINED SAMPLE REGRESSION RESULTS

Dependent variable is: CR2				
$R^2 = 60.1\%$ R^2 (adjusted) = 58.6%				
s = 3.117 with 323 - 13 = 310 degrees of freedom				
Source	Sum of Square	df	Mean Square	F-ratio
Regression	4545.23	12	379.0	39.0
Residual	3012.22	310	9.7168	
MAD Regression	1.461			
MAD Naive	.9412			

tables and normal probability plot of the residuals for the segregated category data set can be found in Appendix B.

The normal probability plot shown in Figure 3 confirms that the residuals are indeed non-normal. To investigate further, Figure 4 plots the externally studentized residuals versus the predicted values obtained in the regression.

This is a better method to examine the residuals, since they are standardized by the estimated standard deviation of the errors with the i^{th} point deleted. Figure 4 shows that as the value of the prediction increases, the dispersion of

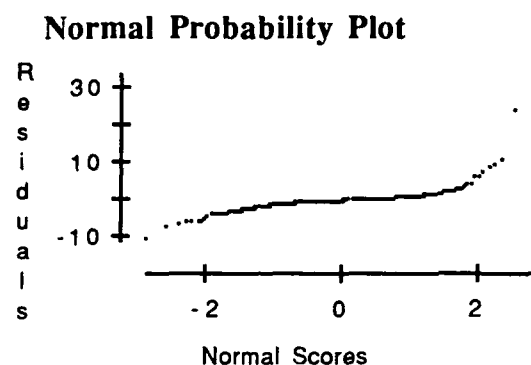


Figure 3 - Probability Plot, Combined Data, Residuals

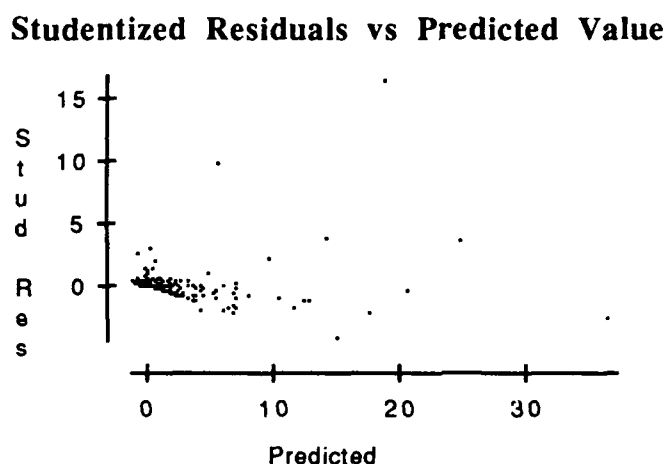


Figure 4 - Studentized Residuals used to Examine Variance of ϵ_i
the errors also increases indicating non-homogeneous variance of the errors [Ref 6:pp. 437-9]. There are two predictions with unusually large error terms indicative of outliers. Upon closer examination the two points with the largest value of studentized residuals have unusual patterns of carcass returns and demand. Both observations have one past quarter observation where carcass

returns is unexpectedly high indicative of a modification or a RFI unit turn-in request from the ICP.

R^2 for the Low and Medium demand regressions were 27.6% and 19.8% respectively. In both cases the errors were obviously not normal. R^2 for the High demand category was better at 58.7%, and the errors appear to be normally distributed which satisfies the regression assumptions. It is not unexpected that the amount of deviation and R^2 is highest for the High demand data since the High demand category has the most variation in the CR1 observations, and defines a much wider range of possible observations than the other two categories. Logically, a deviation of one unit is more significant for the Low and Medium demand categories than for the High category. The MAD in each case is better for the naive model than the regression model .

At this point it does not seem reasonable to use regression for forecasting carcass returns for any category NIINs. The results for the combined sample category items can be slightly improved by adding category variables indicating demand category to the independent variables used in the regression. The results here are disappointing: R^2 became just 60.2%, and the model MAD was lowered to 1.452.

To gain insight into the relationship between the variables, stepwise regression was run for all of the above data sets. As seen in the results of the correlation evaluation in Chapter III, it was not totally surprising to find that there was no predictable pattern concerning the variables which were retained in the model. To forecast CR2 for the Combined sample the model retained DM3, DM5 , DM7, CR4, and CR5. The variables retained in the stepwise regressions on the segregated data sets were: High- CR3, and CR5, Med- DM7,

and DM8, and Low- DM6, and CR3. Therefore, based on these results, it is difficult to access the exact nature of the relationship between demands and carcass returns.

The difficulty with using regression to predict carcass returns is that it not only requires a good size sample, but the regression equation is fit to a wide variety of items. This and the fact that the normality assumption is so clearly violated is most likely why regression does not provide an adequate forecast of carcass returns. Attempts to get a better fit by using the covariates listed in Chapter III, Section A. (eg. wearout rate, Federal Supply Classification, MARK code, etc.) were not successful. Until a better method is available to help group like items, regression will probably not be a viable method for modelling carcass returns. For these reasons, it was decided not to further refine the regression model (eg. introducing higher order terms or fitting a generalized linear model).

B. EXPONENTIAL SMOOTHING

Exponential smoothing is a common forecasting technique, which SPCC currently uses to forecast demand patterns. This technique makes no assumptions about linearity or normality and, in the right situation, can be very powerful. Trend and demand can be incorporated into the model, with simple modifications. It was decided to use exponential smoothing rather than an autoregressive or other time series model because of the nonlinearity and the fact that each series is so short.

Exponential smoothing forecast are typically updated recursively using the current observation of the dependent variable. This allows the model to react quickly when there is a change in the level of the forecast variable. [Ref. 7:pp.

60-1] Typically, a forecaster selects parameters suited for his/her purpose and only changes them when the observations warrant. The approach here is somewhat different, in that the MAD is used to select the best set of parameters in order to forecast the coming quarter. If the model was run in two subsequent quarters it is quite possible that a different parameter set would be selected for the same NIIN. Remember, that the model for this thesis will forecast CR2, and use the MAD minimizing parameter set to forecast CR1. In actuality, the model would use all eight past quarter demand and carcass return observations to obtain the parameters to forecast CR0.

The model in use here is:

$$\widehat{CR}_i = \delta(\alpha CR_{i+1} + (1-\alpha)(\widehat{CR}_{i+1} + Trend_{i+1})) + (1-\delta)DI_{i+1}, \quad i = 2, 3, \dots, 8$$

where

$$Trend_{i+1} = \beta(\widehat{CR}_{i+1} - \widehat{CR}_{i+2}) + (1-\beta)Trend_{i+2},$$

and

$$DI_i = \gamma DM_{i+1} - (1-\gamma)DI_{i+2}.$$

Since the time units are past quarters, the higher the subscript, the older the observation or component of the equation. The parameters α , β , δ , and γ , must be between zero and one, and determine how much weight or emphasis is put on the different variables in the above equations. For example, as the value of α increases, CR_{i+1} , the latest value for CR in time period $i+1$, becomes more important to the forecast. Accordingly, the last forecast and the Trend factor are de-emphasized.

Unlike regression, this model forecasts carcass returns on a NIIN by NIIN basis. This could prove to be very useful for the item manager's carcass return quantity predictions for total costs extensions on repair contracts. Additionally, with the advent of higher speed mainframe computers, SPCC could run the algorithm for items individually, or as a group. The major advantage to exponential smoothing forecast models is that the entire history of an item is contained in the current forecast [Ref. 4:p. 53].

This technique allows for the past history of CR and DM to be used in the prediction of future values of CR. This exponential smoothing model assumes that part of difference between the forecast and actual observation is due to demand, trend, and level with the remaining difference attributable to random chance. Optimum values for α , β , δ and γ can be found by employing the parameter search algorithm written for this purpose and presented in Appendix C. Since there are only eight past quarter DM and CR values, the first period CR and DM observations are used as the first period CR8 and DI8 respectively. The model sequentially generates forecasts for all of the previous periods and picks the parameter set with the lowest MAD averaged over periods 7 through 2. The model then forecasts \widehat{CR}_1 , and calculates the MAD for the particular NIIN. This figure will be used for comparison to the other methods.

To adhere to the integer nature of the data, recognizing that fractional values are unrealistic, two rounding schemes are examined. The first technique is to round up to the next integer if the fractional part of the forecast is greater than or equal to 0.5. This is simply standard rounding practice and can be expected to influence the MAD calculation for a given sample. The second technique is to round up if there is any fractional remainder. This method has

been employed in various inventory situations, with the understanding that it will yield a conservative forecast for the amount of stock necessary to meet demand. If MAD is the criteria, however, this practice will increase the residuals of the forecasts.

In actual use there are two methods for picking the initial forecasts for exponential smoothing models. If sufficient data is available, it would be appropriate to segregate the data into two sets, use the first set to select parameters, and then use the second set to gauge the model's effectiveness [Ref. 4:p. 56]. For example, if a business had two years of weekly demand data available before its initial attempt to utilize exponential smoothing to forecast, the first year's data could be used to adjust the parameters. The forecaster could evaluate several different levels of the smoothing coefficients until he was satisfied he had a set that adequately described his demand pattern. He would then use the selected parameters and see how accurate the model predicted the second year's data. If necessary he would go back and pick a new set of parameters.

This particular case, however, has only 8 data points and the above method would be impractical. Thomopoulos suggests that the first observation for the forecast variable serve as the initial forecast when few data points are available [Ref. 6:p. 61]. This was exactly what was done, using CR8 for \widehat{CR}_8 , DM8 for DI8, and zero for Trend8.

Initially the model was run exhaustively for all possible parameter combinations between zero and one. α and δ were incremented in steps of .05, and β and γ by .01. Each NIIN starts with the parameter set $\alpha = \beta = \delta = \gamma = 0.0$. When the \widehat{CR}_7 is determined, a MAD is calculated using the actual

observation for CR2. This value is compared to the variable MADLOW, which keeps track of the lowest MAD recorded for that NIIN. If the new MAD is lower than the current MADLOW value, the parameter set and forecast are recorded. The loops of the program increment α , β , δ and γ in turn, and calculate a MAD for each possible combination of parameters.

Hillier and Lieberman suggest guidelines to keep α and δ within the range of .1 to .3 to prevent over-smoothing of the data [Ref. 8:p 747]. The model was initially run using the full range (zero to one) for all four parameters, and then run restricting α and δ within the suggested limits. Further references to these models will be as either the full range or the restricted range models. As expected, the full range model picked the $\widehat{CR2}$ MAD minimizing parameter set for each individual NIIN, however, the average MAD for the entire sample (and demand category samples) was higher than the average MAD in the restricted range model. This will be discussed in the next section

C. COMPARISON OF RESULTS

Detailed output listings for both the full and restricted range exponential smoothing models are contained in Appendix D. Table 5 is a description of the column headings for the output. Included in the listings are the MAD minimizing parameter sets, the first period forecast, naive forecast, regression forecast, MAD for each forecast method and the MAD by which the model selected the parameters. The bottom of each table summarizes the significant data for each category sample. These summary statistics are averaged over the number of NIINs in each category. MAD is presented for each forecasting technique and rounding method, but Bias is included for the Naive method and

the standard rounding of the exponential smoothing and regression forecasts only. A cursory review of the summary statistics in each table illustrates that

TABLE 5 - APPENDIX D OUTPUT DESCRIPTION

Column Title	Description
NIIN	self explanatory
HI	1 = High category, 0= Low or Med
LO	1 = Low category, 0= High or Med
CR1	observed value of 1st past quarter CR
DM2	observed value of 1st past quarter DM
Forcst 1st pd	Exponential smoothing forecast, $\widehat{CR1}_i$
δ, α, β , and γ	MAD minimizing parameter set
CR2hat Best MAD	MAD value for parameter selection
MAD 1st Pd	$CR1_i - \widehat{CR1}_i$
MAD Naive	$CR1_i - DM2_i$
Rnd Std	Standard rounding of the ES forecast
Rnd Up	ES forecast rounded up
MAD Std Rnd and Rnd Up	MAD for Rnd Std and Rnd Up
Regress Forecast	self explanatory
Regress Std Rnd/Rnd Up	Regress forecast rounded appropriately
MAD Regress	MAD of unrounded regression forecast
MAD Rg StdRnd/RndUp	MAD Regress Rnd Std and Rnd Up

the "Round Up" method of integerizing the forecasts increases the MAD over that of the Naive method and does not merit further review.

A comparison of the "CR2hat Best MAD" in Tables D1 and D2 shows that although the full range model picked a parameter set with a lower MAD, the category MAD summaries at the end of the tables favor the restricted range model in every case. This is indicative of an over-fitting of the data which introduces additional error when predicting CR1. Further discussions and

comparisons involving exponential smoothing will refer to the restricted range model/output using the standard rounding method only.

Table 6 presents extracted data from Table D2. Notably, the MAD for the exponential smoothing model is lower than that of the Naive or regression models for the combined demand, and each individual demand category. The surprising finding is that the Naive model performed reasonably well, across all demand categories.

In terms of the direction of the forecasting errors, the Bias term in Table 6 indicates that while the exponential smoothing model had a tendency to slightly under-forecast, the other two methods over forecasted. The fact that the exponential smoothing and naive model biases were nearly zero, means that the positive and negative errors nearly cancelled and, adds little information by which to judge effectiveness of forecasts. The regression model bias, however, was somewhat larger and negative and, shows a tendency to over-forecast not present in the other two models. The sample variance of the forecast errors indicates that the variation of the errors for the exponential smoothing and naive methods are somewhat lower than that of the regression model.

The next issue is to determine if there is statistical significance to the differences of the MADs of the different models. It is a simple matter to construct a $(1-\alpha)100\%$ confidence interval of the absolute difference of the forecast errors. The null hypothesis is that there is no difference in the means of the forecast errors, with the alternative being that the null hypothesis is false. Constructing confidence intervals for $\alpha = .05$ and $\alpha = .01$ indicates whether there is a statistical difference in the methods at significance level α . If the confidence interval contains zero there is no significance at level α , and the null

hypothesis cannot be rejected. The standard presentation of the two-sided hypothesis test is shown below. Although this test is structured using the

TABLE 6 - COMPARISON OF FORECASTING TECHNIQUES

Category	Method	MAD	Bias	S ² _{diff}
Combined	ES	0.861	0.012	5.251
	Naive	0.941	-0.200	4.993
	Regression	1.461	- 0.656	10.793
High	ES	2.312	- 0.286	18.112
	Naive	2.506	2.510	15.227
	Regression	3.430	- 1.312	18.248
Medium	ES	0.842	0.140	0.112
	Naive	0.982	- 0.200	2.339
	Regression	1.968	- 1.246	26.824
Low	ES	0.275	0.095	0.222
	Naive	0.291	0.000	0.271
	Regression	0.505	- 0.212	0.416

exponential smoothing and naive methods, all combinations of forecasting methods will be tested.

Formally:

$$H_0: \mu_{ES} - \mu_N = 0$$

$$H_a: \mu_{ES} - \mu_N \neq 0$$

where μ_{ES} and μ_N represent the expected MADs the the respective methods.

The confidence interval is constructed using the formula

$$\widehat{\mu}_{ES} - \widehat{\mu}_N \pm Z_{\alpha/2} \sqrt{\frac{s_{diff}^2}{n}}$$

where $\widehat{\mu}_{ES} - \widehat{\mu}_N$ is the difference in the MADs of the exponential smoothing and naive methods respectively, and s_{diff}^2 is the sample variance of the difference of the forecast errors.

The resulting $(1-\alpha)100\%$ confidence interval $(-0.094, 0.259)$ indicates that the null hypothesis cannot be rejected and that the difference in means is not significant at $\alpha=.05$ [Ref. 9:p. 372]. Confidence intervals, p values, and hypothesis test conclusions for each demand category are presented in Table 7.

In each case, the null hypothesis is the of the same form, with the substitution of the means being tested. The conclusions are based on a 95% confidence interval on the difference in means. The p values in Table 7 indicate that with the exception of the Medium category the null hypothesis can be rejected for the tests concerning the differences between regression and the other methods and that there is no statistical difference between exponential smoothing and the naive method. Except for the size of the confidence intervals, the same results hold for $\alpha = .01$ and are not presented here.

Figure 5 plots the forecast errors of the naive and the exponential smoothing models and shows that the two methods generally err in the same direction. With only a few exceptions the errors lie around the line $y=x$.

Using the the confidence interval formulation above, setting the lower limit equal to zero, and solving for n (using the standard deviation of the set of differences) indicates the sample size necessary for the there to be a statistical significant difference between the exponential smoothing and naive methods of forecasting. For the combined sample this calculation indicates that a sample size of 1,491 items are necessary for the models to be statistically different. The formulation for n is:

$$n = \left(\frac{Z_{\alpha/2} S_{\text{diff}}}{\mu_{\text{ES}} - \mu_{\text{N}}} \right)^2$$

A second random sample of 2,100 NIINs was drawn to verify if this is indeed the case. The new sample size was selected to be conservative and account for any possible differences in variance between the samples. Since

**TABLE 7 - METHOD COMPARISON HYPOTHESIS TESTING
DIFFERENCE IN METHODS $\alpha = .05$**

CATEGORY	MODELS	CI	p	CONCLUSION
Combined	ES-Nav	(-.094,.259)	.362	cannot reject H_0
	ES-Reg	(.316,.887)	.000	reject H_0
	Nav-Reg	(.236,.802)	.000	reject H_0
High	ES-Nav	(-.453,.824)	.570	cannot reject H_0
	ES-Reg	(.500,1.717)	.000	reject H_0
	Nav-Reg	(.335,1.511)	.002	reject H_0
Medium	ES-Nav	(-.189,.476)	.377	cannot reject H_0
	ES-Reg	(-.181,2.439)	.091	cannot reject H_0
	Nav-Reg	(-.316,2.287)	.138	cannot reject H_0
Low	ES-Nav	(-.044,.088)	.521	cannot reject H_0
	ES-Reg	(.157,.315)	.000	reject H_0
	Nav-Reg	(.144,.284)	.000	reject H_0

there was statistical difference between regression and the other model, regression will not be further tested.

Due to the size of the sample, the program in Appendix C was modified to reduce the output. The modified program keeps track of the cumulative differences and the cumulative squared differences between the two methods. This allows for the computation of the mean and variance of the differences. The program output and conclusions are summarized in Table 8 below, and the modified program can be found in Appendix E.

Table - 8 confirms that the techniques are indeed different with the larger sample. Once again, the results for $\alpha = .01$ lead to identical conclusions and

are not presented here. The conclusions in Table 8 only indicate that there is a difference in the two methods. The results of the sample of 323 were certainly

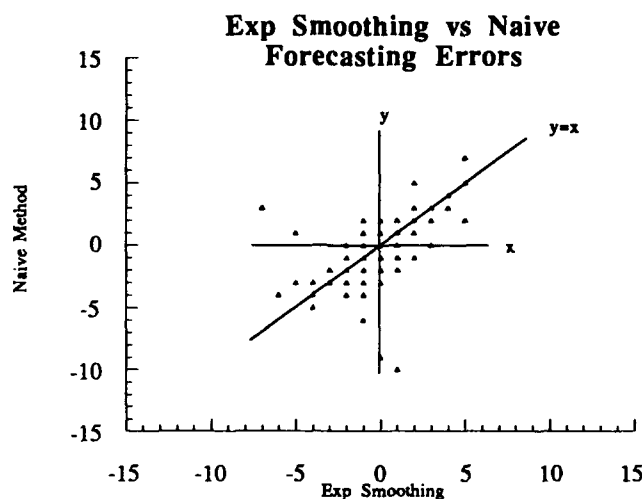


Figure 5 - Forecasting Error Comparison

disappointing, and dilute the dramatic impact of the difference in the methods revealed by the larger sample.

**TABLE 8 - EXPONENTIAL SMOOTHING - NAIVE METHOD
HYPOTHESIS TESTING DIFFERENCE IN METHODS**
 $\alpha = .05$

Category	$\mu_{ES} - \mu_N$	S^2_{diff}	CI	p	Conclusion
Combined	0.131	1.048	(0.174, 0.086)	.000	reject H_0
High	0.346	2.448	(0.487, 0.204)	.000	reject H_0
Medium	0.156	0.496	(0.228, 0.084)	.000	reject H_0
Low	0.041	0.147	(0.062, 0.020)	.000	reject H_0

Although it was necessary to increase the sample size to distinguish between exponential smoothing and the naive models, the results are encouraging. This small difference between the models has practical as well as

statistical significance. The next chapter presents a summary of the thesis and presents conclusions and recommendations for further research.

V. SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

A. SUMMARY

This thesis has examined the relationship between demand and carcass return of repairables at SPCC, and attempted to differentiate between three forecasting methods. Each NIIN had only eight observations for demand and carcass returns, and it was difficult to establish a relationship based on time, since all of the past quarter variables appeared very similar and contained numerous zero observations. Regression, exponential smoothing, and the naive method of forecasting were used to model carcass returns. A comparison of the results indicated that although it was difficult to distinguish between exponential smoothing and the naive method, they each performed better than regression. A larger sample was drawn to reassess the two models with exponential smoothing out-performing the naive method.

B. CONCLUSIONS

SPCC's procurement budget is huge and driven, in part, by the unpredictability of the demand - carcass return process. SPCC has statistical controls on demand, repair survival rate, wearout rate, RTAT, but uses only the demand observation from the past quarter to predict the number of carcasses that will arrive at the DOP for repair. The IM bases his buy decision on the anticipated program growth or decline, and the total number of carcasses, RFI and NRFI, in the system. The accuracy or inaccuracy of any forecast of carcass returns at the DOP obviously affects the number of repairables required

to support a given system at the system command prescribed readiness rates. Generally, the lack of accuracy of any inventory forecast translates into increased safety stock, if the readiness goals are to be achieved.

The extended dollar value of SPCC's annual buys for repairable repair parts is huge, being valued at over \$300 million. It is difficult to access what percentage of these buys are directly attributable to the inaccuracy of the naive forecast driving increased safety stock, but it is apparent that even a small improvement can save a significant amount of money. The difference in the means of the forecast errors of the exponential smoothing and naive method (for the sample of 2100) was 0.131, which extended across the number of SPCC managed repairables experiencing at least one demand in two years (27,731 for purposes of this thesis), could mean an important savings of procurement dollars in an era of fiscal awareness.

C. RECOMMENDATIONS

The results of this thesis imply that it is possible to improve the forecasting of carcass returns at the DOPs, potentially saving money in the process. Conservatively, the use of the exponential smoothing model proposed involves no more risk than the naive model for forecasting carcass returns. This model should be further tested in the real life environment at SPCC. It could be easily incorporated to the IM Workbench, which is a statistical program by which IMs can statistically analyze a NIIN's demand pattern in order to calculate perspective buys.

Attention should be place on evaluation of the difference in performance of the methods with full eight period data compared to the seven period data used for this thesis. The addition of the extra observation would add to the accuracy

of exponential smoothing and do nothing for the naive model. This would differentiate the models even further.

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APPENDIX A

Histograms of Representative Variables from Category Data Sets

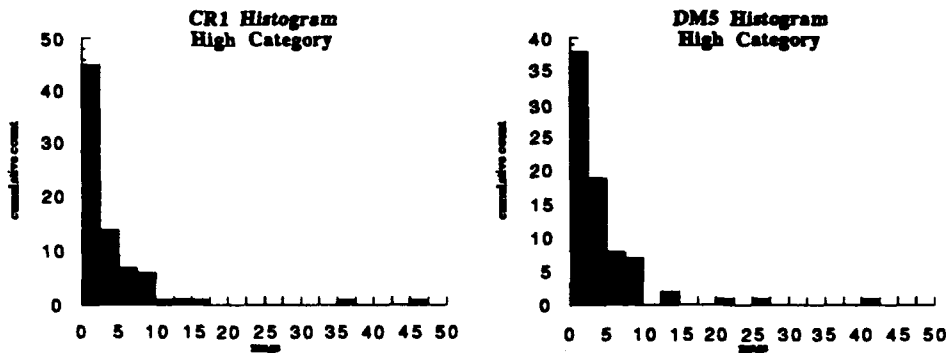


Figure A1- High Demand Category Histograms.

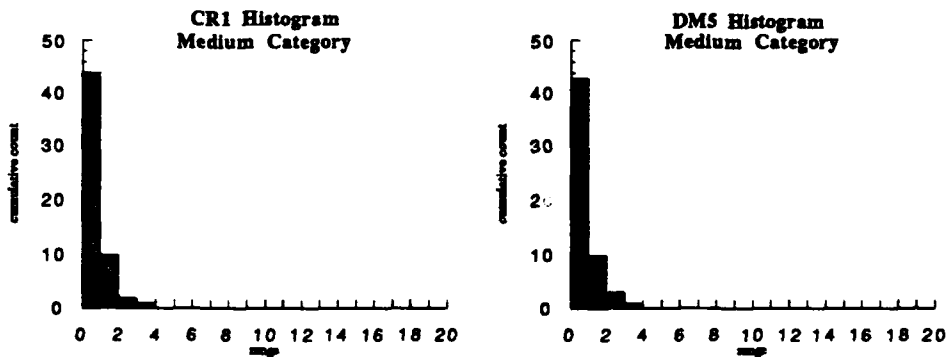


Figure A2 - Medium Demand Category Histograms.

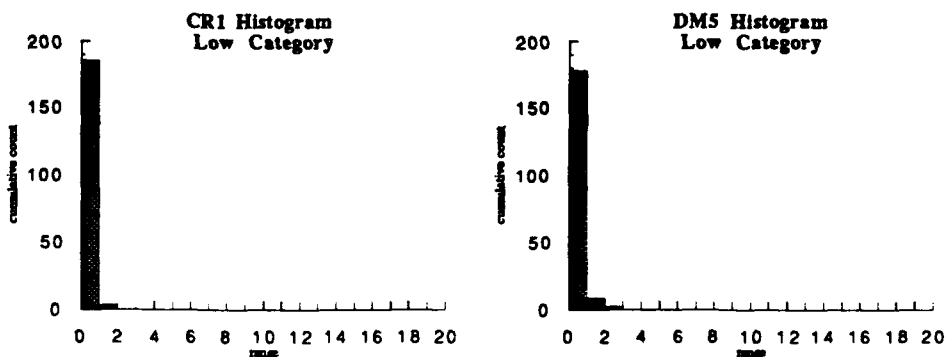


Figure A3 - Low Demand Category Histograms.

APPENDIX B

Regression Output and Plots of Residuals for the Categorized Data Sets

TABLE B1 - HIGH CATEGORY DATA SET REGRESSION OUTPUT

Dependent variable is: CR2				
$R^2 = 58.7\%$ $R^2(\text{adjusted}) = 51.0\%$				
$s = 6.214$ with $77 - 13 = 64$ degrees of freedom				
Source	Sum of Squares	df	Mean Square	F-ratio
Regression	3517.96	12	293.0	7.59
Residual	2471.21	64	38.6126	
MAD Regression	3.911			
MAD Naive	2.506			

**Normal Probability Plot
Residuals, High Data**

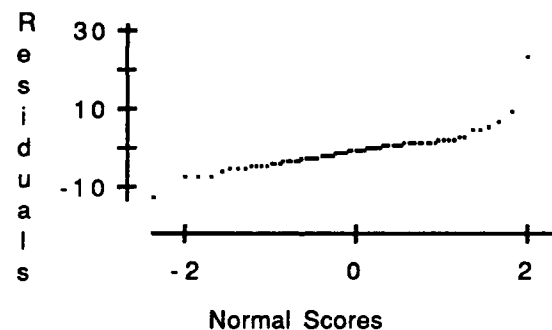


Figure B1- Probability Plot, High Data, Residuals

**TABLE B2 - MED CATEGORY DATA SET REGRESSION
OUTPUT**

Dependent variable is:		CR2		
$R^2 = 19.8\%$		$R^2(\text{adjusted}) = -2.1\%$		
$s = 1.254$		with $57 - 13 = 44$ degrees of freedom		
Source	Sum of Squares	df	Mean Square	F-ratio
Regression	17.0433	12	1.420	0.903
Residual	69.2023	44	1.57278	
MAD Regression	1.653			
MAD Naive	.9824			

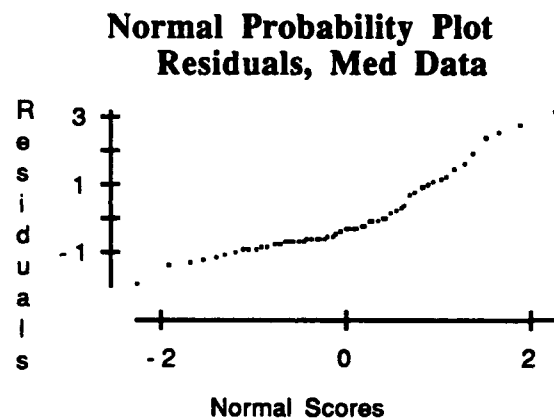


Figure B2 - Probability Plot, Med Data, Residuals

**TABLE B3- LOW CATEGORY DATA SET REGRESSION
OUTPUT**

Dependent variable is: CR2				
$R^2 = 27.6\%$ $R^2(\text{adjusted}) = 22.7\%$				
$s = 0.9172$ with $189 - 13 = 176$ degrees of freedom				
Source	Sum of Squares	df	Mean Square	F-ratio
Regression	56.5824	12	4.715	5.60
Residual	148.063	176	0.841268	
MAD Regression .4385				
MAD Naive .2910				

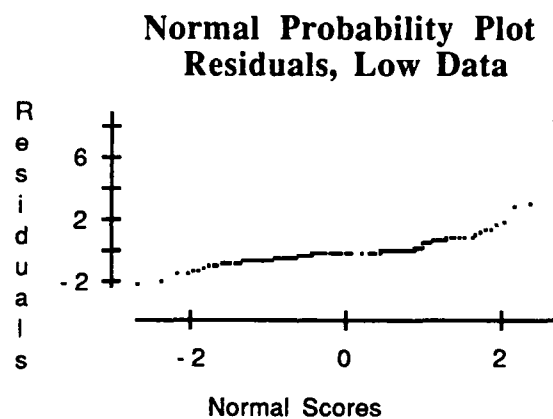


Figure B3 - Probability Plot, Low Data, Residuals

APPENDIX C

Exponential Smoothing Parameter Search Algorithm

```
//EXPLO02 JOB (9003,9999),'EXPLO02 FORTRAN',CLASS=J
//*MAIN SYSTEM=SY2
// EXEC VSF2CG
//FORT.SYSIN DD *
```

```
*****
* Student: Robert B. Vassian, 15 July 1991, Thesis Program *
* Advisors: Prof. Lyn R. Whitaker, CDR David Wadsworth *
* *
* The purpose of this program is to exhaustively search for the MAD minimizing *
* parameter set for the carcass returns of the second past quarter, and then using *
* those parameters, forecast carcass returns for the first past quarter. The *
* program generates an output file for evaluation of the effectiveness of exponential *
* smoothing and the Naive forecasting policies. *
*****
```

```
CHARACTER NIIN(8)*9
INTEGER CR(8), DM(8), PQ(8),MADACT
INTEGER I,K,L,M,N,PQ,HI,LO
REAL A,B,D,G,ALPHA,BETA,DELTA, GAMMA
REAL FOR(9),TREND(8),DI(8),MAD,MADLOW, MAD6

DO 35 K=1,63
  DO 20 I=8,1,-1
    READ(5,51) NIIN(I),PQ(I),DM(I),CR(I),HI,LO
20  CONTINUE
    D=.00
    DELTA =.00
    MADACT=ABS(CR(1)-DM(2))
    MADLOW=1000.0
    DO 23 Q=1,21
      A=.00
      DO 30 L=1,21
        B=.00
        DO 25 M=1,101
          G=.00
          DO 22 N=1,101
            MAD6=0.0
            TREND(8)=0.0
            FOR(8)=CR(8)
            DI(8)=DM(8)
```



```

DO 10 P=7,1,-1
  FOR(P)= D*(A*CR(P+1)+(1-A)*(FOR(P+1)+
&      TREND(P+1)))+(1-D)*(DI(P+1))
  TREND(P)=B*(FOR(P)-FOR(P+1))+(1-B)*TREND(P+1)
  DI(P)=G*DM(P)+(1-G)*DI(P+1)
  IF(P.GT.1) MAD6 =MAD6+(ABS(CR(P)-FOR(P)))/6
10  CONTINUE
  IF(MAD6 .LT. MADLOW) THEN
    MADLOW=MAD6
    MAD=ABS((CR(1)-FOR(1)))
    FORB=FOR(1)
    ALPHA=A
    BETA=B
    GAMMA=G
    DELTA=D
  ENDIF
  G=G+.01
22  CONTINUE
    B=B+.01
25  CONTINUE
    A=A+.05
30  CONTINUE
    D=D+.05
23  CONTINUE
    WRITE(6,48) NIIN(1),HI,LO,CR(1),DM(2),FORB,DELTA,ALPHA,BETA,
&    GAMMA,MADLOW,MAD,MADACT
35 CONTINUE
48  FORMAT(1X,A9,1X,I1,1X,I1,1X,I4,1X,I4,1X,F8.4,1X,F5.3,1X,F5.3,1X,
&    F5.3,1X,F5.3,1X,F8.4,1X,F8.4,1X,I4)
49 FORMAT(A9)
51 FORMAT(A9,I1,I9,I9,I1,I1)
  STOP
  END
/*
//GO.SYSIN DD *
0102166078    0    001 64
0102166077    0    001 64
0102166076    1    101 64
0102166075    0    001 64
0102166074    0    001 64
0102166073    0    001 64
0102166072    0    001 64
0102166071    0    001 64

.

0114898428    0    001 125
0114898427    1    001 125
0114898426    0    101 125
0114898425    1    101 125
0114898424    0    201 125
0114898423    0    001 125
0114898422    1    001 125
0114898421    0    001 125

```

0115320008	0	001 126
0115320007	0	001 126
0115320006	0	001 126
0115320005	0	001 126
0115320004	1	001 126
0115320003	0	001 126
0115320002	0	001 126
0115320001	0	001 126

/*
//

APPENDIX D

TABLE D1 - UNRESTRICTED RANGE EXPONENTIAL SMOOTHING OUTPUT

[illegible]

010692159	1	0	1	0	1	2	1.331	0.05	0	1	0.39	1.3324	0.331	1	1	1	1	2	0	0	1	2.74789	3	3	1.7479	2	2	
010692403	1	0	8	3	3.555	0.5	0	0.45	0.94	1.3457	4.445	1	5	4	4	4	4	4	4	4	4	4	4	4	4	5		
010760313	1	0	1	0	0	0	1	1	0.87	0.91	0.8333	1	1	1	0	0	0	0	0	0	1	0	0	1	0.7349	1		
010777644	1	0	0	0	0	-0.42	0.85	0.3	1	0.98	0.8243	0.42	0	0	0	0	0	0	0	0	1	0	0	2	1.4405	2		
010822929	1	0	0	3	2.945	0.6	0.7	0.94	0.22	0.6387	2.945	3	3	3	3	3	3	3	3	3	3	3	3	3	1	0.772	1	
010847940	1	0	0	0	0	1.999	0.1	0	1	1.3289	1.999	0	0	2	2	2	2	2	2	2	2	2	2	2	1	0.772	1	
010931172	1	0	36	39	39	0	0	0	0	1	4.3333	3	3	39	39	39	39	39	39	39	39	39	39	39	50	2	1.4152	2
011001657	1	0	11	15	20.57	0.75	0.55	1	1	6.6769	18.57	4	4	30	30	30	30	30	30	30	30	30	30	30	20	8.4094	14	
011068907	1	0	3	3	2	8	0	0	0	0	1.5	5	5	1	8	8	8	8	8	8	8	8	8	8	9	13.641	9	
011072139	1	0	3	5	2.5	0.75	1	0	0	1.0417	0.5	2	2	3	3	3	3	3	3	3	3	3	3	3	4	0.3793	4	
011239239	1	0	1	11	0	0	0	0	0	0	0	0	1	10	0	0	0	0	0	0	1	1	1	1	6	7	3.1123	3
011349739	1	0	8	37	22.29	0	0	0	0.1	3.1297	14.29	29	29	22	23	23	23	23	23	23	23	23	23	23	28	19.523	20	
011413747	1	0	5	7	6.484	1	0.05	0	0.19	4.4648	1.484	2	6	7	7	7	7	7	7	7	7	7	7	7	3	4	1.6983	2
011418426	1	0	1	2	1.62	0.95	0	0.68	0	0.3849	5.38	5	5	2	2	2	2	2	2	2	2	2	2	2	2	2	5.1295	5
011480771	1	0	1	2	2.085	0.05	0	1	1	1.1487	1.085	1	2	3	3	3	3	3	3	3	3	3	3	3	2	0.6298	1	
011487985	1	0	13	11	8.254	0.45	0	0.36	1	1.3995	4.746	2	8	9	9	9	9	9	9	9	9	9	9	9	9	9	4.3909	4
011558270	1	0	0	1	4.6	0.85	1	0	0	1.3083	4.6	1	5	5	5	5	5	5	5	5	5	5	5	5	3	2.1033	2	
011623132	1	0	2	4	1.678	0.9	0	0	0.26	0.555	0.678	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	0.3943	0
011628776	1	0	2	4	4.696	1	0.1	1	0.43	2.9806	2.696	2	5	5	5	5	5	5	5	5	5	5	5	5	2	2	0.4577	0
011672553	1	0	3	1	0.96	1	0.3	0.98	0.02	2.4877	2.04	2	1	1	1	1	1	1	1	1	2	2	2	2	2	2	1.9886	1
011720430	1	0	1	1	0.35	0.65	1	0	1	0.725	0.65	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0.0425	0
011797560	1	0	8	5	15	0	0	0	0	8.8333	7	3	15	15	15	15	15	15	15	15	7	7	7	7	17	8.8404	9	
011804442	1	0	1	6	5.12	0	0	0	0.67	1.2239	4.12	5	5	6	6	6	6	6	6	6	4	4	4	4	6	4.5863	5	
011887311	1	0	0	2	2.156	0.85	0.05	1	0.49	0.9889	2.156	2	2	3	3	3	3	3	3	3	2	2	2	2	3	2.3133	2	
011967799	1	0	1	1	0.894	0.25	0	1	0.18	1.2678	0.107	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0.8687	1	
011984125	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-7	7.7247	7	
012083289	1	0	2	4	4.5	0.5	1	0	1	1.1667	2.5	2	5	5	5	5	5	5	5	5	3	3	3	3	4	1.6872	2	
012201819	1	0	0	1	0	1	1	0	0.69	0.8333	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.6018	1	
012272327	1	0	2	0	0	1	1	0	0	0.1667	2	2	0	0	0	0	0	0	0	0	2	2	2	2	2	15	15.34	2
012335262	1	0	7	0	0.012	0	0	0	0.73	6.4305	6.989	7	0	1	1	1	1	1	1	1	7	7	7	7	2	5.5424	6	
012384432	1	0	6	3	1.687	0.95	0	0.43	0.56	2.9673	4.313	3	3	2	2	2	2	2	2	4	4	4	4	4	5	5.4629	5	
012522428	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4753	0	
012552073	1	0	4	4	4.103	0.1	0	1	1	1.4867	0.103	0	4	5	5	5	5	5	5	5	0	0	0	0	5	0.4719	0	
012604045	1	0	0	0	4.983	0.9	0	0	0.88	1.9987	4.983	0	5	5	5	5	5	5	5	5	5	5	5	5	3	2.5631	3	
012615724	1	0	0	0	0	1.074	0.65	0	1	0.7802	1.074	0	1	2	2	2	2	2	2	1	2	2	2	2	3	4	3.295	4
012647594	1	0	4	6	4.252	0.35	0	1	1	0.3341	0.252	2	4	5	5	5	5	5	5	0	1	1	1	1	5	0.9233	1	
012690288	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	1.4068	0	
012719707	1	0	0	2	2.526	0.05	0	0.3	0.73	0.2191	2.526	2	3	3	3	3	3	3	3	3	3	3	3	3	4	5	4.0064	5
000213022	0	0	0	0	0.536	0.85	0.2	1	1	1.12	0.536	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	4.008	0
000308537	0	0	2	0	2	1	0	0.68	0.65	0.8333	0	2	2	2	2	2	2	2	2	0	0	0	0	0	1	1	1.0038	1
001133429	0	0	0	0	0	0	1	0	0	0.3333	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0.8975	1

004751546	0	1	1	0	0.016	0.5	0	0	1	0.3073	0.984	1	0	1	1	0	0.23619	0	1	0.7638	1	0
004751728	0	1	0	1	1	0	0	0	1	0.1667	1	1	1	1	1	1	1	0.22977	0	1	0.2298	0
004909755	0	1	1	0	0	0	0	0	1	0.3333	1	1	0	0	1	1	1	0.11442	0	1	0.8856	1
004918647	0	1	0	3	0	0	0	0	0	0.1667	0	3	0	0	0	0	0	1.87218	2	2	1.8722	2
005034141	0	1	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	-0.0451	0	0	0.0451	0
005251704	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0.18043	0	1	0.1804	0
005384652	0	1	2	0	0	0	0	0	1	0	2	2	0	0	2	2	2	0.13556	0	1	1.8644	2
005938351	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0.95241	1	1	0.9524	1
006026767	0	1	0	0	0.029	0.4	0	0.27	0.05	0.1323	0.029	0	0	0	0	0	1	-0.602	0	0	0.602	0
006248487	0	1	0	1	2.695	1	0.25	0.65	0	1.4186	2.695	1	3	3	3	3	3	3.34373	3	4	3.3437	3
006520668	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.1149	0	0	0.1149	0
006696458	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	-0.1149	0	0	0.1149	0
007051644	0	1	0	0	0	0	0	0	0	0.1667	0	1	0	0	0	0	0	0.10297	0	1	0.103	0
007129548	0	1	1	0	0	0	0	0	0	0.1667	1	1	0	0	1	1	1	0.35374	0	1	0.6463	1
007573287	0	1	0	0	0	0	0	0	0	0.1667	0	0	0	0	0	0	0	-0.2574	0	0	0.2574	0
007778224	0	1	0	0	0.029	0.95	0	1	0.04	0.3333	0.029	0	0	0	0	0	1	0.36173	0	1	0.3617	0
007778768	0	1	0	0	0.37	0	0	0	0.2	0.6509	0.37	0	0	1	0	0	1	0.83366	1	1	0.8337	1
007915607	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	-0.1178	0	0	0.1178	0
008130883	0	1	0	0	0	0	0	0	0	0.1667	0	0	0	0	0	0	0	-0.1319	0	0	0.1319	0
008300312	0	1	0	0	0	0	0	0	0	0.1667	0	0	0	0	0	0	0	-0.4866	0	0	0.4866	0
008638206	0	1	0	0	0	0	0	0	1	0.1667	0	0	0	0	0	0	0	-0.0451	0	0	0.0451	0
008664167	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.1847	0	0	0.1847	0
008838856	0	1	0	0	0	0	0	0	0	0.1667	0	0	0	0	0	0	0	-0.2659	0	0	0.2659	0
008925130	0	1	0	0	0	0.65	1	0	1	0.225	0	0	0	0	0	0	0	-0.1905	0	0	0.1905	0
009166026	0	1	0	0	0.5	0	0	0	0.5	1	0.5	0	1	1	1	1	1	2.06129	2	3	2.0613	2
009168804	0	1	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	-0.0451	0	0	0.0451	0
009355884	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.7073	0	0	0.7073	0
009372452	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	-0.1055	0	0	0.1055	0
009508904	0	1	0	0	1.402	0.9	0	0.94	0	1.8092	1.402	0	1	2	1	1	2	1.33352	1	2	1.3335	1
010036434	0	1	0	0	0.694	0.6	0	0.65	0.87	0.349	0.694	0	1	1	1	1	1	0.43519	0	1	0.4352	0
010090559	0	1	1	0	0	0.4	1	0.25	1	0.5	1	1	0	0	1	1	1	-0.3357	0	0	0.3357	1
0100940751	0	1	0	0	0	0	0	0	0	0.3333	0	0	0	0	0	0	0	-0.2046	0	0	0.2046	0
010124719	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.2659	0	0	0.2659	0
010138069	0	1	1	0	10	1	1	0.08	0	1.6667	9	1	10	10	9	9	9	2.24785	2	3	1.2479	1
010187895	0	1	1	0	0	0	0	0	0	0.1667	1	0	0	0	1	1	1	0.5109	1	1	0.4891	0
010216607	0	1	0	0	0	0	0	0	0	0.1667	0	0	0	0	0	0	0	0.43838	0	1	0.4384	0
010224784	0	1	1	0	0	0	0	0	1	0.3333	1	1	0	0	1	1	1	0.22322	0	1	0.7768	1
010247866	0	1	1	0	0.6	0.6	1	0	1	1.4	0.4	1	1	1	0	0	0	2.5736	3	3	1.5736	2
010274839	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.0451	0	0	0.0451	0
010299405	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	-0.0451	0	1	0.0451	1
010300708	0	1	1	1	1.056	0.9	0.1	0.98	1	0.7291	0.056	0	1	2	0	0	1	1.17549	1	2	0.1755	0

		MAD	MAD	Bias	MAD	MAD	Bias	Bias Rg	MAD	MAD Rg	MAD Rg
		1st Pd	Naive	1stPd Nav	Sid Rnd	RndUp	Sid Rnd	Sid Rnd	Regress	SidRnd	Rnd Up
Average MAD different methods	(whole sample)	1.035	0.941	-0.1	-0.2	1.0402	1.115	-0.1238	-0.6563	1.4606	1.59443
Average MAD different methods	(high category)	2.708	2.506	-0.4	-0.6	2.7273	2.896	-0.4416	-1.3117	3.4301	3.53247
Average MAD different methods	(med category)	0.951	0.982	0.05	-0.2	0.9474	0.982	0	-1.2456	1.9683	2.22807
Average MAD different methods	(low category)	0.378	0.291	0	0	0.381	0.429	-0.0317	-0.2116	0.505	0.61376

TABLE D2 - RESTRICTED RANGE EXPONENTIAL SMOOTHING OUTPUT

[illegible]

010692159	1	0	1	2	1.283	0.1	0.1	0.1	0.41	1.3479	0.283	1	1	2	0	1	2.7479	3	3	1.7479	2	2
010692403	1	0	8	3	3.224	0.1	0.1	0.34	0.58	1.3771	4.776	5	3	4	5	4	2.5753	3	3	3.54247	5	5
010760313	1	0	1	0	0	0.1	0.3	0.75	1	1.6842	1.046	1	0	0	1	1	0.2651	0	1	0.7349	1	0
010777644	1	0	0	0	0	0	0.3	0.18	1	1.0766	0.086	0	0	0	0	0	1.4405	1	1	2.14405	1	2
01082929	1	0	0	3	2.521	0.3	0.3	0.12	0.12	0.7937	2.521	3	3	3	3	3	0.772	1	1	0.772	1	1
010847990	1	0	0	0	0	1.978	0.1	0.1	1	1.3394	1.978	0	2	2	2	2	1.4152	1	2	1.4152	1	2
011001657	1	0	36	39	37.92	0.1	0.3	0	1	4.7226	1.924	3	38	38	2	2	2.4964	50	50	13.641	14	14
011063907	1	0	11	15	17.39	0.3	0.1	1	1	7.3852	6.394	4	17	18	6	7	19.409	19	20	8.4094	8	9
010931372	1	0	3	2	7.923	0.1	0.1	0.14	0	1.6137	4.923	1	8	8	5	5	6.1123	6	7	3.1123	3	4
01072139	1	0	3	5	4.688	0.1	0.3	0	1	1.1976	1.688	2	5	5	2	2	3.3793	3	4	0.3793	0	1
011239239	1	0	1	11	0	0.1	0.1	0	0	0	0	10	0	0	1	1	6.8706	7	7	5.8706	6	6
011349739	1	0	8	37	22.09	0.1	0.3	0	0.1	3.9426	14.09	29	22	23	14	15	27.523	28	28	19.523	20	20
011413747	1	0	5	7	7.699	0.3	0.3	0	1	7.0696	2.699	2	8	8	3	3	3.3017	3	4	1.6983	2	1
011418426	1	0	7	2	1.713	0.3	0.3	0	0.56	1.0597	5.287	5	2	2	5	5	1.8705	2	2	5.1295	5	5
011480771	1	0	1	2	2.115	0.1	0.1	1	1	1.1667	1.115	1	2	3	1	2	1.6298	2	2	0.6298	1	1
011487985	1	0	13	11	8.047	0.3	0.1	0.36	0.72	1.4615	4.953	2	8	9	5	4	8.6091	9	9	4.3909	4	4
011558270	1	0	1	0	1.531	0.2	0.3	0	1	1.8358	1.531	1	2	2	2	2	2.1033	2	3	2.1033	2	3
011623132	1	0	1	0	1.175	0.3	0.3	0	0.6	1.6888	0.175	1	1	2	0	1	1.3943	1	2	0.3943	0	1
011628776	1	0	2	4	3.877	0.3	0.3	0	0.93	3.9613	1.877	2	4	4	2	2	1.5423	2	2	0.4577	0	0
011672553	1	0	3	1	3.126	0.3	0.3	0	0.78	4.7185	0.126	2	3	4	0	1	1.0114	1	2	1.9886	2	1
011720430	1	0	1	1	1.29	0.1	0.1	0.11	0.43	0.7963	0.29	0	1	2	0	1	0.9575	1	1	0.0425	0	0
011797560	1	0	8	5	15.37	0.1	0.1	1	0	8.8604	7.368	3	15	16	7	8	16.84	17	17	8.8404	9	9
011804442	1	0	1	6	5.054	0.1	0.1	0	0.73	1.2335	4.054	5	5	6	4	5	5.5863	6	6	4.5863	5	5
011887311	1	0	2	2	1.998	0.1	0.1	1	0	1.0056	1.998	2	2	2	2	2	2.3133	2	3	2.3133	2	3
011967799	1	0	1	1	0.842	0.15	0.1	0.16	0.16	1.2831	0.158	0	1	1	0	0	1.8687	2	2	0.8687	1	1
011984125	1	0	0	0	0	0.1	0.1	0	0	0	0	0	0	0	0	0	-7.7247	0	-7	7.7247	0	7
012083289	1	0	2	4	4.362	0.3	0.3	1	1	1.2508	2.362	2	4	5	2	3	3.6872	4	4	1.6872	2	2
012201819	1	0	0	1	0.888	0.3	0.3	0	0	0.9919	0.888	1	1	1	1	1	0.6018	1	1	0.6018	1	1
012272327	1	0	2	0	1.772	0.3	0.3	0	0	1.546	0.228	2	2	2	0	0	-13.34	0	-13	15.34	2	15
012335262	1	0	7	0	2.29	0.3	0.25	0	1	6.4402	4.71	7	2	3	5	4	1.4576	1	2	5.5424	6	5
012384432	1	0	6	3	1.999	0.1	0.1	0	0	3.547	4.001	3	2	2	4	4	0.5371	1	1	5.4629	5	5
012522428	1	0	0	0	0	0.1	0.1	0	0	0	0	0	0	0	0	0	-0.4753	0	0	0.4753	0	0
012552073	1	0	4	4	4.123	0.1	0.1	1	1	1.4929	0.123	0	4	5	0	1	4.4719	4	5	0.4719	0	1
012604045	1	0	0	0	1.991	0.3	0.1	1	1	2.5215	1.991	0	2	2	2	2	2.5631	3	3	2.5631	3	3
012615724	1	0	0	0	1.064	0.3	0.1	0.29	0.04	0.9553	1.064	0	1	2	1	2	3.295	3	4	3.295	3	4
012647594	1	0	4	6	4.126	0.3	0.1	1	0.88	0.3764	0.126	2	4	5	0	1	4.9233	5	5	0.9233	1	1
012690288	1	0	0	0	0	0.1	0.1	0	0	0	0	0	0	0	0	0	-1.4068	0	-1	1.4068	0	1
012719707	1	0	0	2	2.526	0.1	0.1	0.07	0.77	0.2315	2.526	2	3	3	3	3	3.40064	4	5	4.0064	4	5
000213022	0	0	0	0	0.748	0.3	0.1	0.99	0.5	1.2138	0.748	0	1	1	1	1	0.4008	0	1	0.4008	0	1
000308537	0	0	2	0	0.325	0.3	0.1	0	0.9	0.8608	1.675	2	0	1	2	1	0.9962	1	1	1.0038	1	1
001133429	0	0	0	0	0.322	0.3	0.1	1	0.74	0.8243	0.322	0	0	1	0	1	0.8975	1	1	0.8975	1	1

004751546	0	1	1	1	0	0.019	0.3	0.3	0	1	0.3281	0.981	1	0	1	0	0.2362	0	1	0.7638	1	0	0
004751728	0	1	0	1	0	1	0.909	0.1	0.1	0	1	0.2029	0.919	1	1	1	1	0.2298	0	1	0	0	
004909755	0	1	1	0	0	0	0	0.1	0.1	0	1	0.3548	1.001	1	0	0	1	0.8856	1	0	1	0	
004918647	0	1	0	1	0	3	0.01	0.1	0.1	0	0	0.1667	0.01	3	0	1	0	1.8722	2	2	1.8722	2	
005034141	0	1	0	0	0	0	1E-04	0.3	0.3	0	1	0.1477	1E-04	0	0	1	0	0.0451	0	0	0.0451	0	
005251704	0	1	0	0	0	0	7E-04	0.1	0.1	0	1	0.1638	7E-04	0	0	1	0	1.1804	0	1	1.1804	0	
005384652	0	1	2	0	0	0	0	0.1	0.3	0.01	1	0.051	2	2	0	0	2	2	1.8644	2	1	1.8644	2
005938351	0	1	0	1	0	1	0	0.1	0.1	0	0	0	0	1	0	0	0	0.9524	1	1	0.9524	1	
006026767	0	1	0	0	0	0	0.002	0.3	0.3	1	0	0.1335	0.002	0	1	0	1	0.602	0	0	0.602	0	
006248487	0	1	0	0	1	1	1.206	0.3	0.3	0.1	0	1.584	1.206	1	1	2	1	2	3.3437	3	4	3.3437	3
006520668	0	1	0	0	0	0	0	0	0.1	0.1	0	0	0	0	0	0	0	0.1149	0	0	0.1149	0	
006696458	0	1	0	0	0	0	4E-04	0.3	0.3	0	1	0.443	4E-04	0	0	1	0	0.1149	0	0	0.1149	0	
007051644	0	1	0	0	0	0	0	0	0.1	0.3	0	0.0358	0	0	0	0	0	0.103	0	1	0.103	0	
007129548	0	1	1	0	0	0	9E-04	0.1	0.1	0	1	0.2014	0.999	1	0	1	0	0.3537	0	1	0.6463	1	
007573287	0	1	0	0	0	0	0	0	0.1	0.1	0	0.1685	0	0	0	0	0	0.2574	0	0	0.2574	0	
007778224	0	1	0	0	0	0	0.02	0.1	0.1	0	0	0.3333	0.02	0	0	1	0	1	0.3617	0	1	0.3617	0
007778768	0	1	0	0	0	0	0.417	0.1	0.1	0	0.24	0.6822	0.417	0	0	1	0	1	0.8337	1	1	0.8337	1
007915607	0	1	0	0	0	0	0	0	0.1	0.1	0	1	0.0333	0	0	0	0	0.1178	0	0	0.1178	0	
008130883	0	1	0	0	0	0	0	0.1	0.1	0	0	0.1685	0	0	0	0	0	0.1319	0	0	0.1319	0	
008340312	0	1	0	0	0	0	0	0.1	0.1	0	0	0	0	0	0	0	0	0.4866	0	0	0.4866	0	
008638206	0	1	0	0	0	0	0	0.1	0.3	0	1	0.1792	0	0	0	0	0	0.0451	0	0	0.0451	0	
008664167	0	1	0	0	0	0	0	0	0.1	0.1	0	0	0	0	0	0	0	0.1847	0	0	0.1847	0	
008838856	0	1	0	0	0	0	0	0	0.1	0.1	0	0	0	0	0	0	0	0.2659	0	0	0.2659	0	
008925130	0	1	0	0	0	0	0	0.1	0.3	0	1	0.3405	0	0	0	0	0	0.1905	0	0	0.1905	0	
009166026	0	1	0	0	0	0	0.596	0.2	0.1	0	0.55	1	0.596	0	1	1	1	2.0613	2	3	2.0613	2	
009168804	0	1	0	0	0	0	1E-04	0.3	0.3	0	1	0.1477	1E-04	0	0	1	0	0.0451	0	0	0.0451	0	
009355884	0	1	0	0	0	0	0	0.1	0.1	0	0	0	0	0	0	0	0	0.7073	0	0	0.7073	0	
009372452	0	1	0	0	0	0	0	0.008	0.1	0.1	0	0.0318	0.008	0	0	1	0	0.1055	0	0	0.1055	0	
009508904	0	1	0	0	0	0	1.011	0.1	0.1	1	0	1.9938	1.011	0	1	2	1	2	1.3335	1	2	1.3335	1
010036434	0	1	0	0	0	0	0.51	0.3	0.1	0.42	0.57	0.4017	0.51	0	1	1	0	1	0.4352	0	1	0.4352	0
010090559	0	1	1	0	0	0	0	0.1	0.3	0.66	1	0.5117	1.016	1	0	0	1	1	1.3357	1	1	1.3357	1
010090751	0	1	0	0	0	0	0	0.1	0.1	1	0	0.3366	2E-04	0	0	0	0	0.2046	0	0	0.2046	0	
010124719	0	1	0	0	0	0	0	0.1	0.1	0	0	0	0	0	0	0	0	0.2659	0	0	0.2659	0	
010138069	0	1	1	0	0	0	1.855	0.3	0.3	0.22	0	1.9211	0.855	1	2	2	1	3	1.2479	1	2	1.2479	1
010187895	0	1	1	0	0	0	0	0.1	0.1	0	0	0.1685	1	0	0	0	1	0.5109	1	1	0.5109	1	
010216607	0	1	0	0	0	0	0	0.1	0.1	0	0	0.1685	0	0	0	0	0	0.4384	0	1	0.4384	0	
010224784	0	1	1	0	0	0	0.008	0.1	0.1	0	1	0.3655	0.992	1	0	0	1	0.2232	0	1	0.2232	0	
010247866	0	1	1	0	0	0	0.137	0.3	0.3	0	1	1.69	0.863	1	0	1	1	2.5736	3	3	1.5736	2	
010274839	0	1	0	0	0	0	0	0.1	0.1	0	0	0	0	0	0	0	0	0.0451	0	0	0.0451	0	
010299405	0	1	1	0	0	0	0	0.1	0.1	0	0	0	0	1	1	0	1	1	1.0451	1	1	1.0451	1
010300708	0	1	1	1	0	1	0.436	0.3	0.1	1	0.54	0.8668	0.564	0	1	1	0	1.1755	2	0	1.1755	0	

		MAD	MAD	Bias	MAD	MAD	Bias		Bias Rg	MAD	MAD Rg	MAD Rg
		1st Pd	Naive	1stPd Nav	Sid Rn-1	RndUp	Sid Rnd		Sid Rnd	Regress	SidRnd	Rnd Up
Average MAD different methods	(whole sample)	0.859	0.941	0.01	-0.2	0.8667	1.077	0.0124	-0.6563	1.4606	1.306502	1.59443
Average MAD different methods	(high category)	2.321	2.506	-0.3	-0.6	2.3117	2.519	-0.2857	-1.3117	3.4301	3.12987	3.53247
Average MAD different methods	(med category)	0.839	0.982	0.13	-0.2	0.8421	0.912	0.1404	-1.2456	1.9683	1.842105	2.22807
Average MAD different methods	(low category)	0.269	0.291	0.09	0	0.2751	0.54	0.0952	-0.2116	0.505	0.402116	0.61376

APPENDIX E

Modified Exponential Smoothing Parameter Search Algorithm for Large Sample Size

```
//EXPPRG1 JOB (9003,9999),'EXPPRG1 FORTRAN',CLASS=J
//*MAIN SYSTEM=SY2
// EXEC VSF2CG
//FORT.SYSIN DD *
```

```
*****
* Student: Robert B. Vassian, 12 August 1991, Thesis Program *
* Advisors: Prof. Lyn R. Whitaker, CDR David Wadsworth *
* * *
* This program is the exhaustive search routine for the for the larger *
* sample. The program finds the MAD minimizing parameter set for each *
* NIIN but only returns the cumulative differences and cumulative *
* squared differences. Calculations are also made for the naive method *
* and are returned upon completion of the run. *
*****
```

```
CHARACTER NIIN(8)*9,NIN*9
INTEGER CR(8), DM(8), PQ(8),HI(8),MADACT, XI,XISQ,HXI,LXI,MXI
INTEGER HXISQ,MXISQ,LXISQ,DIFF,DIFFH,DIFFM,DIFFL,MADES
INTEGER I,K,L,M,N,P,Q,FORR,HIGH,LOW,MED
REAL FOR(9),A,B,D,G,ALPHA,BETA,DELTA,GAMMA,DI(8),TREND(8)
REAL MAD,MADLOW,MAD6,MADN
REAL NXI,NXISQ,HNXI,HNXISQ,LNXI,LNXISQ
REAL MNXI,MNXISQ,MCH,MCHN,MCM,MCMN,MCL,MCLN
```

```
C      DO 15 T=1,14400
C      READ(2,45) NIN
C 15 CONTINUE
```

```
      DO 35 K=1,300
      MADES= 0
      FORR=0
      DO 20 I=8,1,-1
        READ(2,51) NIIN(I),PQ(I),DM(I),CR(I),HI(I)
20    CONTINUE
        D=.10
        DELTA =.10
        IF(HI(1) .EQ. 10)THEN
          HIGH = HIGH+1
        ELSEIF(HI(1) .EQ. 01)THEN
          LOW=LOW+1
```

```

ELSE
    MED = MED+1
ENDIF
MADACT=ABS(CR(1)-DM(2))
MADLOW=1000.0
DO 23 Q=1,5
    A=.10
    DO 30 L=1,5
        B=.00
        DO 25 M=1,101
            G=.00
            DO 22 N=1,101
                MAD6=0.0
                TREND(8)=0.0
                FOR(8)=CR(8)
                DI(8)=DM(8)
                DO 10 P=7,1,-1
                    FOR(P)= D*(A*CR(P+1)+(1-A)*(FOR(P+1)+
&                TREND(P+1)))+(1-D)*(DI(P+1))
                    TREND(P)=B*(FOR(P)-FOR(P+1))+(1-B)*TREND(P+1)
                    DI(P)=G*DM(P)+(1-G)*DI(P+1)
                    IF(P.GT.1) MAD6 =MAD6+(ABS(CR(P)-FOR(P)))/6.0
10                CONTINUE
                IF(MAD6 .LT. MADLOW) THEN
                    MADLOW=MAD6
                    IF((FOR(1)-(REAL(INT(FOR(1))))).GE. 0.5) THEN
                        FORR = INT(FOR(1)) +1
                        MADES= ABS(CR(1)-FORR)
                    ELSE
                        FORR = INT(FOR(1))
                        MADES= ABS(CR(1)-FORR)
                    ENDIF
                ENDIF
                G=G+.01
22            CONTINUE
            B=B+.01
25        CONTINUE
        A=A+.05
30    CONTINUE
    D=D+.05
23 CONTINUE
MAD=MAD+REAL(MADES)
MADN=MADN+REAL(MADACT)
DIFF=ABS(ABS(MADES)-ABS(MADACT))
XI=XI+DIFF
XISQ=XISQ+DIFF**2
IF(HI(1).EQ.10)THEN
    MCH = MCH+REAL(MADES)
    MCHN= MCHN+REAL(MADACT)
    DIFFH = DIFF
    HXI=HXI+DIFF
    HXISQ=HXISQ+DIFF**2
ELSEIF(HI(1).EQ.01) THEN
    MCL = MCL+REAL(MADES)

```

```

        MCLN = MCLN+REAL(MADACT)
        DIFFL =DIFF
        LXI=LXI+DIFF
        LXISQ=LXISQ+DIFF**2
    ELSE
        MCM=MCM+REAL(MADES)
        MCMN=MCMN+REAL(MADACT)
        DIFFM=DIFF
        MXI=MXI+DIFF
        MXISQ=MXISQ+DIFF**2
    ENDIF

35 CONTINUE
    WRITE(6,49) XI,XISQ,K, DIFF
    WRITE(6,50) MAD/(K-1),MADN/(K-1)
    WRITE(6,46) HXI,HXISQ,HIGH, DIFFH
    WRITE(6,50) MCH/REAL(HIGH),MCHN/REAL(HIGH)
    WRITE(6,47) MXI,MXISQ,MED, DIFFM
    WRITE(6,50) MCM/REAL(MED),MCMN/REAL(MED)
    WRITE(6,48) LXI,LXISQ,LOW, DIFFL
    WRITE(6,50) MCL/REAL(LOW),MCLN/REAL(LOW)

49 FORMAT(1X,' XI = ',I9,' XISQ = ',I14,' K = ',I5,' D ', I5 )
46 FORMAT(1X,' HXI = ',I9,' HXISQ = ',I14,' HIGH = ',I5,' D ', I5 )
47 FORMAT(1X,' MXI = ',I9,' MXISQ = ',I14,' MED = ',I5,' D ', I5 )
48 FORMAT(1X,' LXI = ',I9,' LXISQ = ',I14,' LOW = ',I5,' D ', I5 )
45 FORMAT(A9)
50 FORMAT(1X,'MADCUM = ',F15.4,' MADCUMN = ',F15.4)
51 FORMAT(A9,I1,I9,I9,I2)
    STOP
    END
/*
//GO.FT02F001 DD DISP=SHR,DSN=MSS.S9003.EXPSAM
//

```

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